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Assessing impact of the COVID-19 pandemic on China's TFP growth: Evidence from region-level data in 2020

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ABSTRACT

This paper examines the first wave spread of COVID-19 in China and its impact on TFP growth for 2020, and assess the role of anti-epidemic lockdown policy in suppressing the pandemic. Methodologically, we systematically quantify the disparity in the pandemic's productivity impact and the role of lockdown policies across regions, by combining the prefecture-level TFP growth for 422 regions (including 276 municipal cites and 146 county regions) with the daily statistics on the pandemic. Our results show that the negative impact of the COVID-19 pandemic on TFP growth are more likely to occur in municipal cities, compared to rural areas. Moreover, the anti-epidemic quarantine policy succeeded to bring the COVID-19 pandemic down in China, but it may generate additional costs through dampening TFP growth if overused. Given the regions either with a relative higher resilience level or in the remote rural areas suffered more from the strict regulation. A more flexible policy is required to be designed so as to mitigate the ongoing COVID-19 impacts in future. These findings provide useful insights for China, as well as other Asian developing countries, to cope with its continuing episodes.

1. Introduction

The outbreak of the Coronavirus Disease 2019 (COVID-19) pandemic has spread rapidly across Asia and the world since the late 2019, imposing unprecedented challenges to health, livelihood, and economies throughout the world (Baldwin and Weder di Mauro, 2020; Laborde et al., 2020; Dixon et al., 2021). First identified in Wuhan, China, in December 2019 and declared a global pandemic by the World Health Organization (WHO) in March 2020, the COVID-19 has gradually evolved into a serious global public health crisis. Due to its high level of infectivity and wider spread across regions, the COVID-19 pandemic has tragically caused over 6.2 million deaths and over 510 million people infected up to April 2022 and continued to increase its casualty throughout the world (WHO, 2021). Beyond mortality and morbidity, the pandemic has also triggered global economic contraction, imposing an increasing challenge for the world to achieve the UN Sustainable Development Goals (SDG) in 2035. Early estimates indicate that the pandemic could cause a doubling of the severely undernourished population and a surge in extreme poverty (FAO, 2020; FSIN, 2020; HLPE, 2020) and major contractions

of global and many national economies (World Bank, 2020). Updated analysis shows that the pandemic caused global growth in 2020 to fall by 3.5 percent, recording the worst recession since the Great Depression, and surpassing the Global Financial Crisis (IMF, 2021).

To fight against the COVID-19 pandemic, many countries initially have imposed a wide range of strong public health actions, including restrictions on local, domestic and international movements of people, promotion of strict hygiene and social distancing measures, and population-wide free vaccine programs, drawing in part on lessons from earlier viral pandemics (Peeri et al., 2020; CCSA, 2020). While these efforts helped to save a large number of lives in the early stages of the pandemic when no vaccine is widely available, they also incurred a substantial amount of economic and social costs which in turn were induced in many regions. As the new and more highly infectious variates (i.e. Delta virus, FE and RE) were recurring across the world since 2021 and high infection rates were continuing for the third year globally, more and more people were thinking that the government should balance the efforts for fighting against the pandemic spread in the short run and for dealing with other widespread sustainable development challenges that had intensified in the interim. However, for most developing countries throughout the Asia Pacific region, where medical services per capita are in scarcities, it is still a hard decision to make. In particular, it requires public policy makers to rethink how to find a new and more effective way out to manage downside risks caused by the ever-lasting pandemic and safeguard gains in economic growth and hard-won reduction in poverty over the pre-pandemic period.

As a pioneer and practitioner of anti-epidemic quarantine policies, China has firmly adopted such a policy consistently from the very beginning of the pandemic, and it succeeded in controlling the first wave of spread of the COVID-19 in 2020. Three important policy measures, including the quick government response and policy intervention, the strict anti-epidemic quarantine policies and enforcement, and the well-organized subsistence support system are attributed to be the most efficient tools that have been used by the central government to make the achievement. From 1 December 2019 to 20 May 2020, China managed to fully control the spread of the COVID-19 within 150 days with 123,642 confirmed infection cases and 5,688 deaths (WHO, 2021), and presented the fastest recovery among every single country in the world. While China's GDP is estimated to decline about 0.4% to 0.8% compared to normal in 2020 (with an average drop of about 2% in short-term consumption; an average drop in employment of about 0.7%) (Wu et al., 2021), both economic and social costs are much lower than other countries. In particular, when the second and subsequent waves of the pandemic hit by 2021, the country has almost maintained its normal operation, which in turn demonstrates the strong resilience of the system. Chinese success in 2020 gave the incentive and confidence for other Asian developing countries to adopt anti-epidemic lockdown policies. However, little is known about whether Chinese-style anti-epidemic policies would be the most efficient way to fight against the pandemic and whether Chinese experience could be shared by other developing countries. Meanwhile, it is also a question of how such a policy could be better used when the pandemic becomes an everlasting event.

This paper aims to examine the impact of the first-wave COVID-19 pandemic on total factor productivity (TFP) in China, with a particular focus on different roles of the strict anti-epidemic quarantine policies in rural and urban areas in fighting against the pandemic. Methodologically, we conduct a three-step econometric analysis by using daily pandemic statistics and TFP growth for 422 regions (including 276 municipal cities and 146 county regions) in 2020 in China. Specifically, we first examine the economic impact of the COVID-19 pandemic by regressing region-level TFP growth on infection cases in 2020. Then, we construct an index to quantify the anti-epidemic lockdown policies and examine the effectiveness of the anti-epidemic lockdown policies in fighting against the COVID-19 pandemic in rural and urban areas. Finally, we also make use of cross-region heterogeneity to specify criteria that could be used to balance between anti-epidemic lockdown policies and other more flexible measures to fight against the COVID-19 effects.

Our results show that caseloads of COVID-19 infections are obviously negatively correlated with TFP growth at the national level, suggesting that the COVID-19 negatively affects economic growth in the long run through dampening TFP growth. The quarantine policy is initially an efficient policy against the pandemic, but the economic benefit of imposing the anti-epidemic quarantine policy is to be offset by its shutdown effects. This implies that for a country or a region to successfully adopt the quarantine policy to fight against the pandemic, it should be used in a flexible way. This is a particular important experience for urban areas than for rural areas. Finally, we also show that increasing the resilience of the production system to the pandemic is a better way, than only imposing the anti-epidemic quarantine policy, to cope with the challenges caused by the everlasting pandemic. This is not only because regions that are exposed to more frequent external TFP shocks are more resistant to the pandemic shock, but also because they are more likely to realize the effectiveness of quarantine policies.

Our paper contributes to the literature at least in two ways. First, our study is the first to examine the productivity impact of the COVID-19 in China, with a focus on the comparison between municipal cities and rural regions. In literatures, there have been many studies examining direct economic impacts of COVID-19 including consumption and income (Wu et al., 2021; Chen et al., 2020) but little is known on the productivity impact of this crisis. We fill the gap by investigating how the pandemic and the anti-pandemic policy may affect TFP growth across regions. Second, our study distinguishes between the different roles of anti-pandemic policies in urban and rural areas, and highlights the importance of improving the resilience of production systems to cope with the everlasting pandemic in urban areas. Our productivity analysis in China shows that increasing the resilience of production systems for health emergency events is more important than only imposing the anti-epidemic quarantine policies in fighting against the pandemic. This finding, beyond doubt, can also provide useful insights for other Asian developing countries to make more effective public policy measures for post-disaster socio-economic recovery.
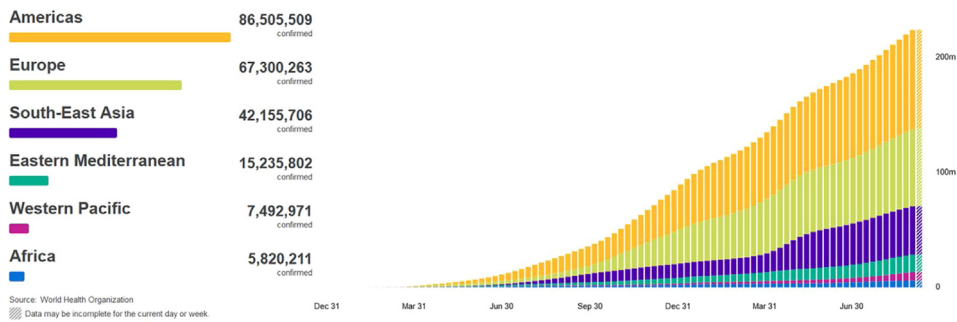
Fig. 1. The dynamic evolvement of total number of infected COVID-19 cases by region.
Source: WHO (2021)

The rest of the paper is organized as follows. Section 2 summarizes the background on the first-wave COVID-19 pandemic in China, its potential health and social impact and the corresponding policy response. We discuss the proposed empirical specifications and data used for the empirical exercise in Section 3. Section 4 provides an empirical analysis and the results of the productivity impact of COVID-19 and assesses the role of anti-epidemic quarantine policies in the fight against pandemics, followed by a more general discussion in Section 5. Section 6 provides the conclusion.

2. Background

First identified in Wuhan, China, in December 2019 and declared a global pandemic by the World Health Organization (WHO) in March 2020, the cumulative number of reported COVID-19 cases increased to 84 million globally by December 2020, which makes the pandemic the most critical global public health crisis in recent years. Given its nature of the high level of infectivity and the long duration, the respiratory infectious disease has caused an unprecedented level of health and economic cost worldwide. According to the latest statistics, there are more than 224 million people infected, with over 4 million deaths throughout the world between March 2020 and September 2021 (Fig. 1) (WHO, 2021), and the reported COVID-19 infected caseloads and its induced social and economic losses continue to increase in many countries. Beyond mortality and morbidity, the pandemic has also triggered global economic contraction, and thus impose new challenges in meeting the UN sustainable development goals (Dixon et al., 2021; Fan and Otsuka, 2021). Policymakers expect that the COVID-19 would severely reduce productivity and food security, especially for poor people (HLPE, 2020; UNESCAP, 2020). While there is still no accurate estimate available, UNESCAP (2021) analysis shows that, due to the pandemic, there will be an increase of 89 million extremely poor and an overall 1% contraction of the regional economy in Asia and the Pacific region only, representing major setbacks for development in the region.

China was the first country to be hit heavily by COVID-19, but quick government actions and strictly imposed anti-epidemic quarantine policies helped to control the first-wave of the pandemic in the absence of vaccines in 2020. From 3 January 2020 to 20 May 2020, the cumulative number of reported COVID-19 infection cases was 123,642 and the reported mortality was 5,688 (WHO, 2021) in China, ranking top globally by then. In response to the sudden onset of the COVID-19, China immediately implemented very strict movement restrictions including nationwide lockdowns and relief programs (first in Wuhan, and then extend to Hubei province and national wide). The quick action of the government and the strong enforcement of movement restrictions prevented the virus from spreading across regions. Fig. 2 shows the change of the reported infected, dead, healed and suspected cases for the period of 1 December 2019 to 20 May 2020, the net number of infected cases (equal to the newly infected minus healed) peaked at approximately Day 80 or around 3 weeks after the lockdown policy was first implemented in Wuhan on 23rd January (followed by many provinces activating the Level-one response to major public health emergencies). Thereafter, the net number of infected cases from the first-wave pandemic gradually leveled off and then fell to zero by late May 2020, when the national-wide movement restriction is abolished. Throughout 2020, the nationwide spread of the pandemic had been well controlled within the first 150 days, and the majority of infected cases were confirmed in Wuhan (see Fig. 2B) and the total infected cases averaged only one-third of the Asian average and one-tenth of the global average.

Apart from the aggregate efforts made by the central government to fight against the first-wave COVID-19 pandemic, local governments (in particular, those at city levels) demonstrate different capacities for implementing the anti-epidemic quarantine policies and thus generate different consequences. Unlike Wuhan, where the large-scale local transmission had emerged for a while, other cities were faced with a similar situation in which their efforts were mainly put to prevent the spread of COVID-19 from Wuhan city (or the Hubei province). Thus, their strategies also focused on identifying the imported cases as soon as possible and confining local nobilities. Although local authorities were all fully motivated to curb the transmission after witnessing that both the secretary of the provincial committee in Hubei and the secretary of the city committee in Wuhan were removed from office on February 13th due to their inability to contain the transmission, the effects indeed varied. As it is shown in Fig. 3, both the lengths of duration and the peak number of infected cases were

A) The accumulated number of infected, healed, dead and suspected cases at daily basis: 2019-12-01 to 2020-05-20
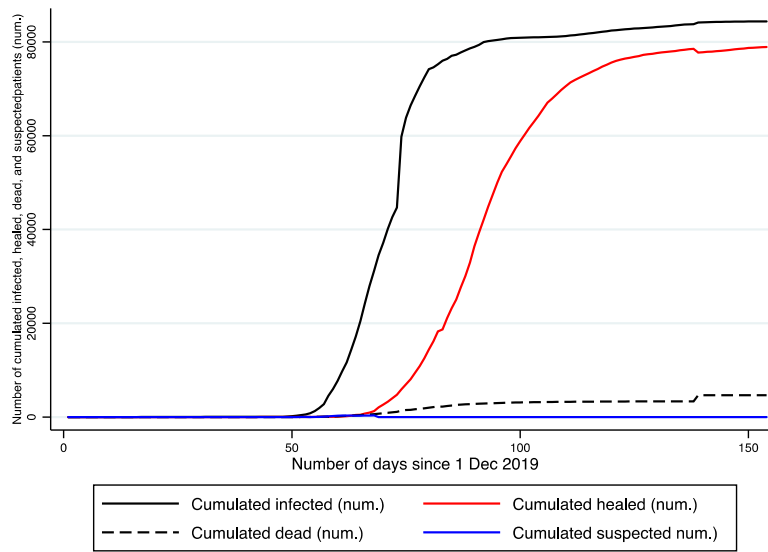
B) The accumulated number of net infected cases at the Nation level and in Wuhan at daily basis: 2019-12-01 to 2020-05-20
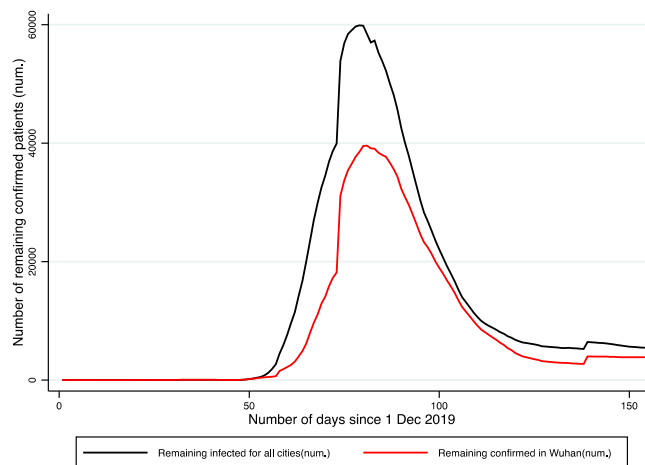

Fig. 2. Dynamic evolution of the COVID-19 pandemic in China in 2020.
Source: Authors' own estimation

quite different in these cities. This is mainly due to differences in the ability of local authorities to mobilize resources and social organizations. The diverse performance of different cities in resilience against the COVID-19 outbreak, and between rural and urban areas, exposes key factors and issues that need particular attention for economic recovery and the next pandemic disaster (Chen et al., 2021).

While succeeded in bringing the first-wave COVID-19 pandemic under control and shifting to a "new normal" situation, China has also paid huge social and economic costs, either due to the direct loss caused by the pandemic or to the indirect costs associated with the lockdown policies. At the national level, China's GDP is estimated to decline about 0.4% to 0.8% due to the first-wave COVID-19 pandemic compared to normal in 2020, with an average drop of about 2% in short-term consumption and an average drop in employment of about 0.7% (Wu et al., 2021). It is also to be noted that the first-wave COVID-19 pandemic reduced China's real income by 19.4% in the first quarter of 2020, with 272 out of 315 cities experiencing a decline in real income (Chen et al., 2020). Meanwhile, some recent studies suggest that TFP growth in China
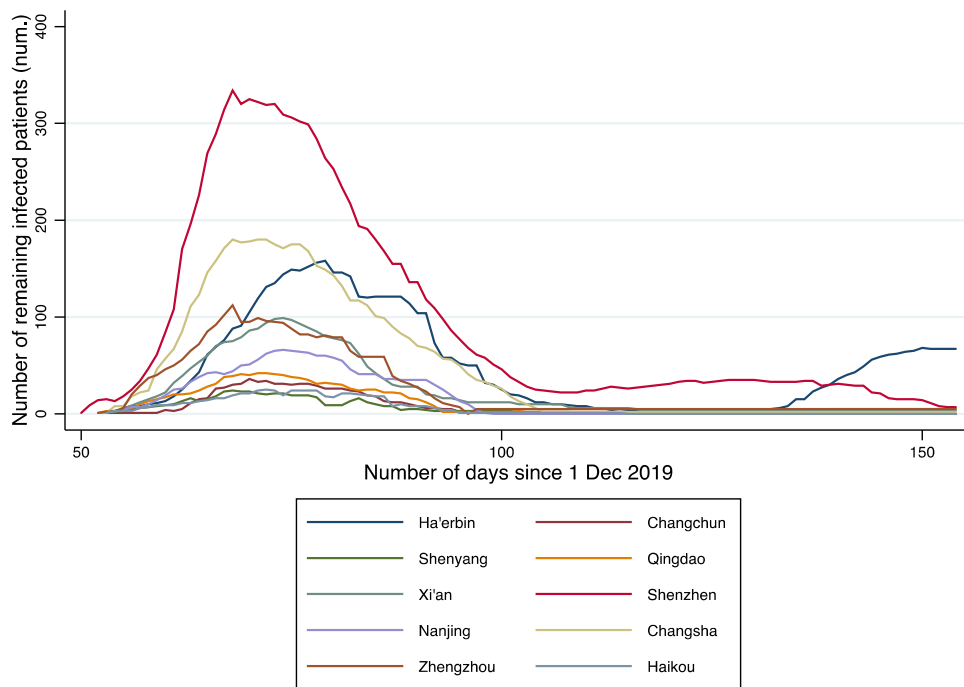
Fig. 3. The accumulated number of net infected cases for 10 selected cities.
Source: Authors' own estimation

may also be eroded by increased transaction costs, reduced mobility, and narrower reallocation of resources between sectors and regions (Mauro and Syverson, 2020; Baldwin and Weder di Mauro, 2020).

To date, many studies have been devoted to examine the COVID-19 pandemic and its potential impact on economic development from different perspectives. For example, Chen et al. (2020) estimated city-level real income losses in China in 2020 after the COVID-19 outbreak and revealed a high heterogeneity across regions in China: Wuhan (and its neighboring regions) experienced a 60.4% decline in real income, while the median city experienced an average 19.7% decline in real income. In another study, Wu et al. (2021) also found that the COVID-19 pandemic and its induced movement restrictions had generated a substantial negative impact on employment and thus interrupted the rural-to-urban transformation through migration. Despite efforts put into the short-term economic analysis of the COVID-19, little is known about the long-term impact of this crisis and in particular the consequence on TFP growth.

Sustainable productivity growth has long been at the center of public concerns throughout the world, as it matters more for long-term economic growth than other factors for both developed and developing countries. Before the outbreak of the COVID-19, the world had already suffered 15 years of a productivity growth slowdown. Although there might be a slight chance of productivity gains from teleworking (Bloom et al., 2015; Morikawa, 2020) or positive impulses from induced innovation during the quarantine, there is more of concerns that the pandemic itself and the restrictions to contain transmission (including quarantines, social distancing practices, mobility restrictions, etc.) may further impair productivity growth by causing higher transactions costs (Baldwin and di Mauro, 2020) and reducing the scale of resource reallocation across firms, sectors, and countries (di Mauro and Syverson, 2020). However, how the COVID-19 and the anti-epidemic policies may affect total factor productivity growth (or technology progress) of a country is still to be understood. This calls for more thorough empirical studies based on the existing data released to the public.

Looking back on the Chinese experience of fighting against the pandemic in 2020, the long-run dynamic and asymmetric effects of the COVID-19 are presenting differently across regions. However, more is to be understood from re-examining the difference in productivity performance across regions and between in urban and rural areas when using the pandemic as a natural experiment. On the one hand, whether the regions with certain characteristics showed more resilience in TFP when faced with impact remains still unclear. On the other hand, although China succeeded to control the initial wave of COVID-19, it is not known whether the anti-epidemic quarantine policies may be the best choice for an economy facing other development issues. Thus, a closer scrutiny on region-level data can provide important knowledge on understanding these mechanisms and assessing the effectiveness of policy measures in combating the pandemic.

3. Empirical methods and data sources

3.1. Empirical model specifications

Theoretically, the COVID-19 pandemic can affect TFP growth through many channels. As an unexpected external shock, the COVID-19 pandemic is first expected to directly reduce the efficiency of the production system, either directly through increased production costs related to infection or through causing chaos. In addition, the anti-epidemic policies initiated by the government to bring the COVID-19 pandemic under control, such as movement restriction, social distancing policies, and other red-tape regulations, also disrupted the market channels for input supplies and output sales, intensifying the market risk for production. While the expansion of public support and social protection programs may have helped boost demand for particular commodities such as food and other necessities (i.e. face masks and detergent etc.), they generally could not offset the efficiency loss of the production system. Taking agricultural production in China as an example, the widespread disruptions of harvesting and marketing of perishables, e.g., aquaculture, horticulture, and reduced product prices were greater than good grain delivery to cities, which combined to reduce agricultural productivity and farmers' income (Dixon et al., 2021). Depending on the resilience of individual production system, the productivity impact of the COVID-19 could differ substantially across regions and between urban and rural areas, and so does the effects of anti-epidemic lockdown policies.

In order to examine the impact of the first-wave COVID-19 pandemic on TFP growth in China and the corresponding anti-epidemic lockdown policies in fighting the pandemic, we propose a three-step procedure. The first starts with regressing the logarithm of region-level TFP growth on the measure of the COVID-19 shocks, with the control of its initial TFP level. The baseline model is assumed to take the form of:

$$\Delta \ln TFP_i = \beta_0 + \gamma \ln TFPlag_i + \beta_1 \ln Infe_i + \beta_2 \ln Cure_i + \beta_3 \ln Dead_i + \alpha Z_i + \varepsilon_i \tag{1}$$

where $\Delta \ln TFP_i$ denotes the change in the logarithm of TFP level for region i between 2019 and 2020 and $\ln TFPlag_i$ denotes the logarithm of TFP level for the same region in 2019. Using the lagged logarithm of TFP level as the control variable allows us to remove the region-specific characteristics that could affect its TFP growth. $\ln Infe_i$, $\ln Cure_i$, and $\ln Dead_i$ denoted the indicators for accumulated infected, healed, and dead cases respectively, which are jointly used to capture the severity of the COVID-19 pandemic in each region. Z_i represent other factors that could affect region-level TFP growth, which include the regional population size, economic scale and industrial structure, etc. We use them as control variables to eliminate the impact of other time-variant factors that could cause the potential endogeneity problem. Finally, ε_i is a random error term.

Eq. (1) can be estimated by using the generalized least square (GLS) approach. With the control of other factors, the estimated coefficients in front of $\ln \_Infected_i$, $\ln \_Cured_i$, and $\ln \_Dead_i$ can be used to measure the average impact of the COVID-19 pandemic on TFP growth across regions in China. For example, if the estimated coefficient of $\ln \_Infected_i$ is negative and significant, it implies that the COVID-19 pandemic will impose a negative impact on regional TFP by increasing the accumulated infected cases, and vice versa. A similar argument also applies to other variables including $\ln \_Cured_i$ and $\ln \_Dead_i$.

Although the baseline model provides useful insights on how the COVID-19 pandemic may affect average TFP growth in China, it will not help to inform whether the pandemic will generate heterogeneous productivity impacts across regions, in particular between in urban and rural areas. In particular, it is believed that urban and rural areas may respond differently to the COVID-19 pandemic. Meanwhile, the pandemic will also impose different impacts on TFP growth in the regions with different levels of resilience (OECD, 2020, 2021; Dixon et al., 2021). To explore answers to this question, we next split our sample into two groups: namely, 276 municipal cities and 146 county regions, and categorize regions in each group by their resilience levels (such that x < 33%, 33% < x < 66% and x > 66%). The potential assumption is that the COVID-19 pandemic may impose different impacts on urban and rural areas and on the regions with different resilience levels.

We distinguish between urban and rural areas by using the concept that whether the region belongs to one of 276 municipal cities, and measure the resilience of a region by using the coefficient of variance of region-level TFP from 1978 through 2019. The null hypothesis is that the region with a relatively higher coefficient of variance of TFP is usually suffering more external shocks which is more likely to have a higher capacity to adapt to the COVID-19 shock, which is consistent with OECD (2020). The measure not only reflects resilience in the economic term but is also related to rural resilience in particular since the rural production system is more likely to be exposed to external productivity shocks. With the additional assumptions to cope with cross-regional disparities, we reformulate Eq. (1) into

$$\Delta \ln TFP_{rgi} = \beta_0 + \gamma \ln TFPlag_{rgi} + \beta_1 \ln Infe_{rgi} + \beta_2 \ln Cure_{rgi} + \beta_3 \ln Dead_{rgi} + \alpha Z_{rgi} + \varepsilon_{rgi} \tag{2}$$

where $g = 1, 2, 3$ denotes the sub-group samples with relatively lower, middle and higher resilience levels respectively and other notations are same as in Eq. (1).

Eq. (2) can be used to measure the different impacts of the COVID-19 pandemic on TFP growth in urban and rural areas and across regions with different resilience levels (or adaptive capacities). A comparison of these measured TFP impacts will also inform how different types of regions may cope with the COVID-19 shock in different ways, especially when the pandemic becomes an everlasting event. In addition to using Eq. (2), we have also conducted a robustness check by pooling all the samples together while incorporating two dummy variables for the regions with the middle and higher

resilience levels and their interaction terms with the COVID-19 shocks. The purpose is to conduct the F-statistical test for the cross-group difference.

In addition to measuring the productivity impact of the pandemic, we have also assessed the role of the anti-epidemic quarantine policy in fighting against the COVID-19 and restoring region-level productivity. To achieve the goal, we further propose two additional regression models.

One model is to regress the indicators for the COVID-19 pandemic such as the accumulated infected, healed, and death cases on the stringency of the implemented anti-epidemic lockdown policy, such that

$$\ln COVID19_i = \beta_0 + \beta_1 \ln Lock_i + \beta_2 \ln Locksq_i + \alpha Z_i + \varepsilon_i \tag{3}$$

where $\ln COVID19_i$ represent the COVID-19 pandemic including $\ln Infected_i$, $\ln Cured_i$, and $\ln Dead_i$. $\ln Lock_i$ and $\ln Locksq_i$ denote the measure of anti-epidemic lockdown policy and its square term. For generality, the square term of the measure of anti-epidemic lockdown policy is included in Eq. (3) to capture the potential non-linear policy effects. Meanwhile, we also compare the estimated results with the linear function form as a robustness check.

The other model is to regress the logarithm of the predicted impact of the COVID-19 shock (or $\widehat{\Delta \ln TFP_i}$), estimated using Eq. (1) on a measure of the stringency of the implemented anti-epidemic lockdown policy, such that

$$\widehat{\Delta \ln TFP_i} = \beta_0 + \beta_1 \ln Lock_i + \beta_2 \ln Locksq_i + \alpha Z_i + \varepsilon_i \tag{4}$$

where $\widehat{\ln TFP_i}$ denotes the predicted impact of the COVID-19 shock, and $\ln Lock_i$ and $\ln Locksq_i$ denote the measure of anti-epidemic lockdown policy and its square term.

The estimation of Eqs. (3) and (4) provides the average impact of the implemented anti-epidemic lockdown policy and its underlying channels through which the impacts are imposed. Finally, we also conduct the estimation of Eqs. (3) and (4) by using the sub-group samples, so that the different roles of anti-epidemic lockdown policy in fighting against the COVID-19 shock between urban and rural areas and among the regions with different resilience levels can be distinguished.

For all the above regression analyses, we adopt the general method of moment (GMM) approach to resolve the potential endogeneity problem that could be caused by using the GLS regression. Both the second (e.g. variance) and third moments (e.g. kernel density) have been used as the instrumental variables to identify the independent variables in use. Meanwhile, both the first-wave COVID-19 pandemic shock and the government-imposed anti-epidemic lockdown policy are imposed for public health concerns, and thus they can be more safely regarded as relatively exogenously to TFP growth.

3.2. Data source and major variable

The data used in this study mainly come from two sources. One data source is China County Statistical Yearbook, which provides the production account data (including capital, labor, intermediate inputs, and the gross output) for 422 regions in China between 1949 and 2020. These regions include 276 municipal regions and 146 county-level regions with population and GDP above a certain level, and the production account statistics cover both agricultural and non-agricultural production activities in urban areas and in the neighboring rural areas. The data obtained from this source are used to estimate the region-level TFP levels, the coefficient of variance for each region between 1978 and 2019, and other region-level control variables used in the regression analyses.

The other data source is the public release of real-time crawler statistics (DXY, 2021) on the COVID-19 pandemic from WHO, Chinese Center for Disease Control and Prevention (China CDC), and local media, which provides the information on the accumulated number of infected, dead, healed, and suspected cases for each county on the daily basis for the first wave of the COVID-19 pandemic between 1 December 2019 and 20 May 2020. The data obtained from this data source are used to measure the indicators for the COVID-19 shocks and the anti-epidemic lockdown policies when they are combined with the population mobility index. Combining the two data sources and eliminate the sample with incomplete information, we obtain a sample of 323 regions. Finally, we ditched out Wuhan from our sample as an outlier generating the final dataset in use containing 322 regions.

Region-level TFP is the most important dependent variable used in this study. We measure region-level TFP by using a semi-parametric approach based on the value-added model. In literatures, for example, Olley and Pakes (1992); Levinsohn and Petrin (2003); Ackerberg (2016); Wooldridge (2009), the regression-based productivity may usually suffer from a potential endogeneity problem, caused by a positive correlation between labor and capital input. To resolve this problem, we adopt a two-stage procedure following Ackerberg et al. (2006) and Wooldridge (2009), which relies on the assumption that the idiosyncratic shocks to productivity in each period t do not affect that producer's choice of the level of the state variable (i.e., investment), but only the choice of free variables (i.e., labor and material inputs). Specifically, the first stage is to regress output $q_{it} = ln\left(\frac{R_{it}^j}{P_{it,bb}}\right)$ on a flexible function of inputs (l_{it}, m_{it}, k_{it}) (where $l_{it} = \ln\left(\frac{L_{it}}{W_{it}}\right)$, $m_{it} = \ln\left(\frac{M_{it}}{P_{it,bb}^M}\right)$ and $k_{it} = \ln(\frac{K_{it}}{r_{it}})$) so as to use the information of investment (i_{it}) or other external instruments to identify productivity.

$$q_{it} = \varphi_{\varphi,t} (l_{it}, m_{it}, k_{it}, i_{it}) + \varepsilon_{it} \tag{5}$$

Table 1
Descriptive statistics for the major variables in use: 362 regions in 2020.
Source: Authors' own estimation.

	Num. of Obs.	Mean	Std. Dev.	Min	Max
Relative TFP of 2020 to 2019 (RTFP)	422	1.005	0.003	1.000	1.010
Infected COVID-19 Effects (log)	422	7.500	1.445	4.369	12.628
Healed COVID-19 Effects (log)	422	7.080	1.769	0.000	12.314
Dead COVID-19 Effects (log)	422	1.123	2.241	0.000	9.205
Coefficients of Variance (TFP)	422	0.305	0.008	0.280	0.327
Quarantine Measure (Kurt/Length)	422	0.086	0.070	0.018	0.433

where region-level TFP is estimated as

$$\omega_{it} = \widehat{\varphi_{\varphi,it}} - f_{\varphi t}(l_{it}, m_{it}, k_{it}, i_{it}; \beta) \tag{6}$$

Using Eqs. (5) and (6) for TFP estimation requires the use of the process that determines productivity movements over time. In this case, we use an exogenous Markov process such that

$$\omega_{it} = g_{\varphi}(\omega_{i,t-1}, \widehat{X_{it}}) + v_{\varphi it} \tag{7}$$

where region-level productivity and its movements vary across different production technologies.

Estimation of the production function coefficients β relies on assumptions about how regions change input use in response to random productivity shocks over time $v_{\varphi t}$. When various inputs are assumed to adjust with productivity shocks at different speeds, the identification conditions can be quite different.

We allow regions to dynamically choose both labor and capital but adjust the use of intermediate inputs only when productivity shocks arrive. This assumption can be summarized in a moment condition as follows

$$E\left[v_{\varphi it}(\beta) \begin{pmatrix} l_{it} \\ m_{it-1} \\ k_{it} \end{pmatrix} \right] = 0 \tag{8}$$

The condition in Eq. (8) is flexible and allows for a variety of production functions with different assumptions about the variability of inputs and the use of instruments.

The COVID-19 shocks are the key independent variables used in our study. In literature, the common practice is to use either the number of infected cases or the accumulated number as approximates. Although transparent, such measures could not reflect the impairment of the COVID-19 shocks. Instead, we measure the COVID-19 shocks by first depicting the density function of the accumulated number of infected, dead, healed, and suspected cases for the whole period and then measuring the areas underlying the density function over time as indicators. These measures are more likely to reflect the COVID-19 shocks from the perspective of consequence. The potential assumption underlying this measurement is that each infected, dead, healed and suspected case will incur the costs throughout the whole pandemic period.

The measure of anti-epidemic lockdown policy is another key independent variable used in our study. We measure the anti-epidemic lockdown policy in two alternative ways. One is based on the strictness of mobility restriction and is constructed by using the Baidu Urban Vitality index (Baidu, 2019, 2021). The index ranges between 0.238 and 10.710, with the larger the index, the less mobility restricted. The other is based on the consequence of mobility restriction. Since the anti-epidemic lockdown policy is adopted to control the COVID-19 pandemic, we can measure the stringency of the policy by using a measure on how quickly the daily net infected cases fall into zero. Specifically, we define the measure as a ratio of the kurtosis of the net number of infected cases to the length of the real pandemic period for each region as an approximate. The higher the index is, the quicker the COVID-19 pandemic is to be brought under control.

Other control variables also include total population, total GDP, and the relative proportion of secondary and tertiary industries in gross output value at the region level. Table 1 provides the summary statistics on the major variables for the 362 regions in China for 2020.

4. Empirical results

In this section, we discuss the empirical results based on the empirical strategy proposed in Section 3. In particular, we will first look at the apparent relationship between the COVID-19 shocks and region-level TFP growth, and then examine the impact of the pandemic on TFP growth for 2020 between in urban and rural areas in China and by regions with different resilience levels. Finally, we will access different roles of the anti-epidemic lockdown policy in fighting against the COVID-19 pandemic across regions.

4.1. Apparent relationship between the COVID-19 shock and region-level TFP in China

Fig. 4 depicts the apparent relationship between regional-level TFP in China and the COVID-19 shocks measured by using the accumulated number of infected, dead, healed, and suspected cases. To capture the non-linear relationship
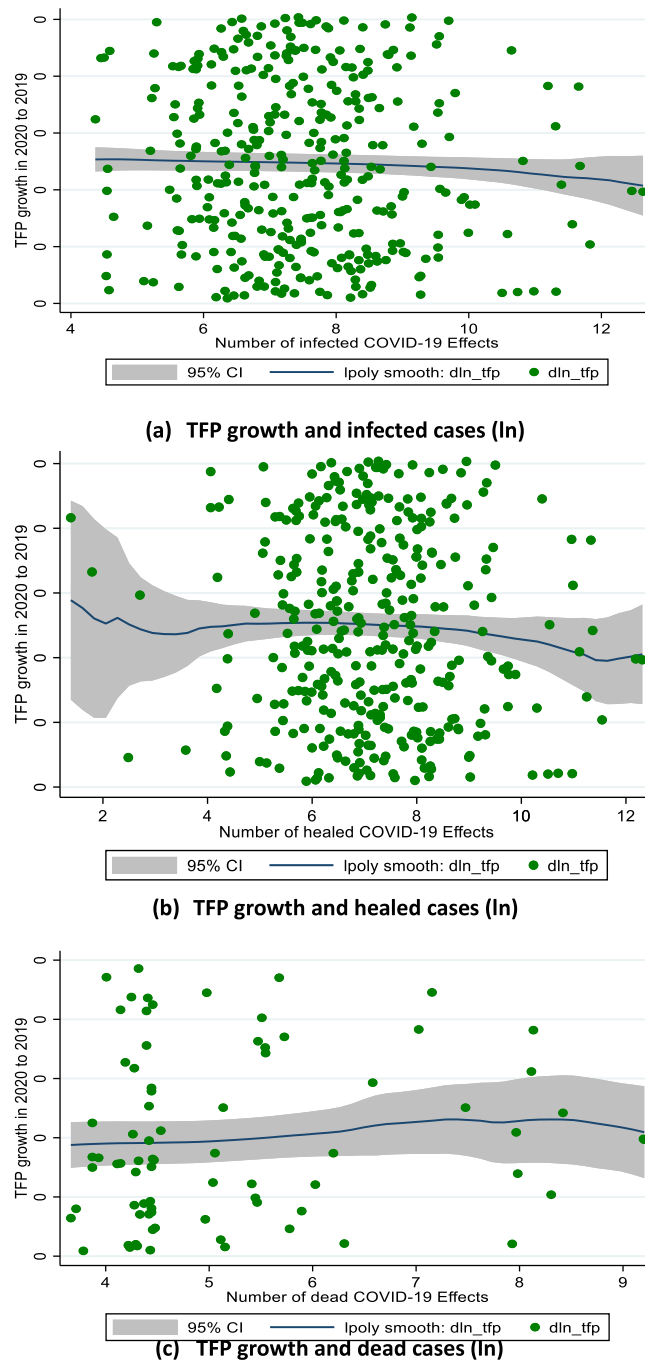
(a) **TFP growth and infected cases (ln)**

(b) **TFP growth and healed cases (ln)**

(c) **TFP growth and dead cases (ln)**

Fig. 4. Apparent relationship between TFP growth and the COVID-19 shocks.
Source: Authors' own estimation.

between regional-level TFP in China and the COVID-19 shocks, we use the LOWESS function to fit the data. Generally, the accumulated number of infected and suspected cases are negatively related to region-level TFP growth in China, but the relationship between the accumulated number of healed and dead cases and region-level TFP growth is uncertain. In practice, the uncertain relationship between the accumulated number of dead cases and the COVID-19 is out of expectation, since one may think that the fatal ratio will be more detrimental to productivity growth. A possible explanation for the phenomenon is that different measures of the COVID-19 shocks could interact to generate a joint impact on region-level TFP.
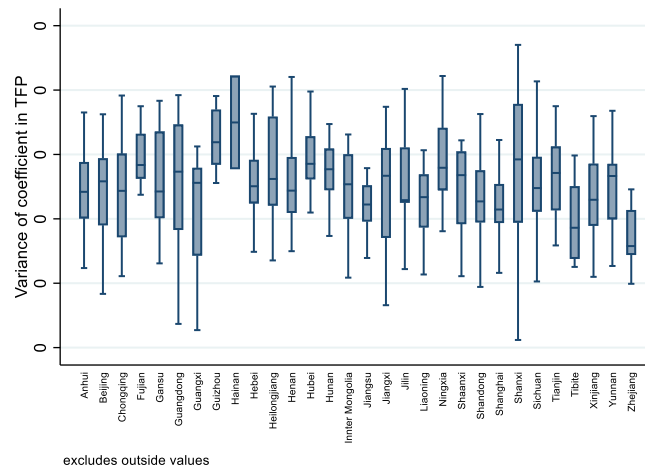
Fig. 5. Boxplot of region-level resilience (coefficients of variance) across region.
Source: Authors' own estimation.

Moreover, we calculate the coefficients of variance of TFP for the 422 regions in China by using the historical TFP for the period of 1978–2019 and use them as a measure of the resilience of each region. As it is shown in Fig. 5, the boxplot of coefficient of variance over time shows a huge cross-region disparity of productivity variation in China before the COVID-19 shock, suggesting that some regions in China have been exposed to more frequent productivity shocks than other regions in history. Assuming that the regions facing more frequent productivity shocks are more likely to form their adaptive capacities, they are expected to cope with the COVID-19 shock more easily. Thus, we split our sample regions into three equal subgroups according to the coefficients of variance of region-level TFP, for both urban and rural areas.

Fig. 6 compares the relationships between region-level TFP growth in 2020 and the COVID-19 shocks measured by using the accumulated number of infected cases, between urban and rural areas and across the regions with different resilience levels. Two interesting findings are worth mentioning. First, the negative impact of the COVID-19 shocks and TFP growth is much stronger in municipal cities than in rural areas. This implies that the adverse impact is more likely to occur in the more populated regions. Second, while region-level TFP growth in 2020 is negatively related to the COVID-19 shock measures for all the three sub-group regions according to their resilience levels, the negatively relationship for the sub-regions with more resilience is much stronger than for the other two sub-groups regions. This implies that TFP growth in the more resilient region are less likely to be dampened by the COVID-19 shock.

Although the above analyses have provided some useful information on the impact of the COVID-19 shocks, the visual analyses are heavily influenced by regional characteristics and interactions between different COVID-19 measures. Therefore, a more thorough empirical study is required to conduct by using the regression analyses, assuming that the COVID-19 pandemic is an exogenous shock.

4.2. Impact of the COVID-19 on region-level TFP in China

Applying Equations (1) and (2) to the data of region-level TFP growth and the COVID-19 shock measures, we estimate the average impact of the pandemic on region-level TFP growth in 2020. The regression results, obtained from using the whole sample of 422 regions and from using those sub samples between urban and rural areas and by regions with different resilience levels, are reported in Table 2. Columns (1)–(2) of Table 1 provides the estimated the COVID-19 impacts on aggregated TFP growth in 2020 with and without the control of province cluster effects, while columns (3)-(4) provides the estimated COVID-19 impacts on TFP growth for rural and urban regions and columns (5)-(7) for different types of regions by resilience levels.

First, the COVID-19 pandemic has on average imposed a negative impact on region-level TFP growth in China, but only through a certain mechanism. With the control of region specific characteristics and other productivity determinants, the estimated coefficients in front of the COVID-19 pandemic measured by using the accumulated number of infected and dead cases are both negative and significant at 5% level, while the estimated coefficients in front of the accumulated number of healed cases are positive and significant at 1% level. This result implies that the COVID-19 pandemic negatively affects region-level TFP growth in 2020 through worsening the social health status and increasing the fatal rate. However, a better medical service and a high cure rate helps to offset the negative TFP impact of the COVID-19 pandemic. As an evidence, the estimated coefficient of the pandemic measure based on the number of suspected cases are insignificant at 10% level. In other words, the COVID-19 pandemic may generate negative impact on region-level TFP growth in China through increasing infection rates and death rate.
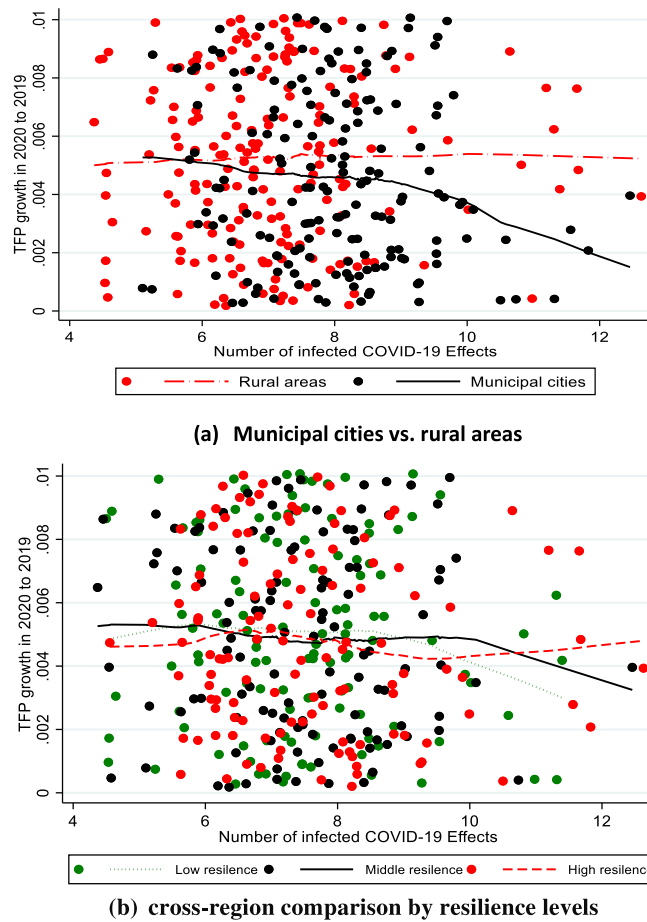
(a) Municipal cities vs. rural areas

(b) cross-region comparison by resilience levels

Fig. 6. TFP growth and the COVID-19 shocks between urban and rural areas, and across the regions with the high, middle and low resilience levels.
Source: Authors' own estimation.

Table 2
Impact of COVID-19 on TFP at the region level in China.
Source: Authors' own estimation.

	All Sample		Rural vs. Urban		By resilience levels		
	Base	Cluster	Rural	Urban	LowR	MidR	HighR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: TFP growth in 2020 (ln)							
TFP level in 2019 (ln)	−0.090	−0.090	−0.818	0.618	−0.600	1.750	−1.310
	(0.650)	(0.640)	(0.963)	(0.916)	(2.910)	(1.920)	(1.820)
Infected num. effects (ln)	−0.030	−0.030**	−0.044	−0.028*	−0.04*	−0.020	−0.030
	(0.020)	(0.010)	(0.324)	(0.015)	(0.02)	(0.010)	(0.020)
Healed num. effects (ln)	0.030**	0.030***	0.054	0.028***	0.05***	0.030***	0.010
	(0.010)	(−0.003)	(0.323)	(0.000)	(−0.006)	(−0.003)	(−0.009)
Dead num. effects (ln)	−0.020**	−0.020**	−0.000	−0.033***	−0.030*	−0.030***	−0.002
	(−0.008)	(0.01)	(0.000)	(0.000)	(0.02)	(0.010)	(0.020)
Constant	0.600	0.600	1.320	0.130	1.130	−1.380	2.030
	(0.690)	(0.720)	(1.060)	(0.010)	(3.08)	(1.980)	(1.950)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster effect (province)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. of Observations	422	422	276	146	122	118	122
R-squared	0.031	0.031	0.014	0.077	0.057	0.064	0.032

Note: TFP growth refers to the growth of TFP between 2019 and 2020. Robust standard errors in parentheses, and "***", "**" and "*" represent *p* < 0.01, *p* < 0.05 and *p* < 0.1 respectively.

Second, when we compare the impact of the COVID-19 pandemic on region-level TFP growth between urban and rural areas and among the regions with different resilience levels, we show that the negative TFP impact of the pandemic are more likely to occur in municipal cities, while they are declining as the resilience level of regions increases. As is shown in Columns (3)-(4), the estimated negative TFP impact of the COVID-19 pandemic is only significant at 10 percent level for the municipal cities. Moreover, the significant level of the estimated coefficients in front of the COVID-19 pandemic shocks measured by using the accumulated number of infected and dead declines when the resilience level of regions increases, as is shown in Columns (5)-(7). In particular, the estimated coefficients under the COVID-19 pandemic shocks for the regions with the highest resilience levels become insignificant at 10% level. The result implies that the COVID-19 shock is more likely to generate a substantial negative impact on region-level TFP growth in municipal cities in China and for the region used to confront limited productivity shocks in the past. A possible explanation on this phenomenon is that: the regions used to confront more frequent productivity shocks over the past four decades may have formed a better spontaneous system adapting to external productivity shocks, and thus they can maintain better productivity growth performance in response to the COVID-19 shock. A useful insight obtained from this finding that: increasing the adaptive capacity of production system is one of the best ways for a region to fight against external shocks like the COVID-19 pandemic.

In sum, the COVID-19 pandemic generally imposes a negative long-term impact on region-level TFP growth in China through increasing the infected and dead cases, in addition to its short-term social and economic welfare effects. However, the negative productivity effects are more likely to occur in municipal cities with low resilience levels. This highlights the importance of increasing the adaptive capacity to fight against the COVID-19 shock when the duration of the pandemic increase.

4.3. The role of anti-epidemic lockdown policy in fighting the COVID-19 pandemic

The anti-epidemic quarantine policy is widely believed to be one of the most effective policies to control the COVID-19 pandemic, in particular before the vaccine is available to the public. In this sense, how efficient the policy is in fighting against the COVID-19 pandemic and inducing economic costs deserve more empirical analyses, and the results may provide useful policy implications. In this subsection, we examine the role of the anti-epidemic quarantine policy in alleviating the pandemic's impact on TFP growth, and the results are shown in Tables 3 and 4. Three interesting findings are found based on our regression analyses.

First, the anti-epidemic quarantine policy is negatively affecting the spread of the COVID-19 pandemic. As is shown in Table 3, the estimated coefficients under the pandemic measures are negative and significant at 1% level when we regress the accumulated number of infected, suspected and dead cases (also see Fig. 7). This result implies that the lockdown policy is an effective policy that helped to bring down the first-wave pandemic in China. In particular, the stricter the policy is enforced, the less the number of infected and dead cases would be. Our finding is generally supporting the conclusion of previous studies on the pandemic's economic effect (Bin et al., 2021; Ozili and Arun, 2020; Huang et al., 2021), which argued that the lockdown policy contributes to the recovery of environment and economy and is beneficial to TFP growth.

Second, the anti-epidemic quarantine policy may impose a mixed impact on region-level TFP growth, when facing the COVID-19 pandemic. Specifically, while a moderate imposition of lockdown policy does help to improve region-level TFP growth, a harsh lockdown policy may do harm to region-level TFP growth. As shown in Table 3, the estimated relationship between the stringency of the anti-epidemic lockdown policy and region-level TFP growth takes an inversed "U"-shaped curve, as the estimated coefficients in front of the anti-epidemic lockdown policy and its square term are positive and negative (with both of them being significant at 1% level). This implies that region-level TFP has first increase with the imposition of anti-epidemic lockdown policy in China and then decrease when the stringency of the lockdown policies increases to a certain level. However, the inverted "U"-shaped relationship implies that the positive effect of TFP growth occurs only if the quarantine policy is moderate. This result is consistent with our expectation since the overuse of the lockdown policy will disrupt the market supply and thus negatively affect the productivity of firms and/or farms.

Third, when we analyze the different roles of the anti-epidemic quarantine policy in affecting region-level TFP growth across the regions with different resilience levels, we show that the regions with higher adaptive capacities are more likely to benefit from a more flexible lockdown policy. As is shown in Columns (3) and (4), the inversed "U"-shaped relationship between the stringency of the anti-epidemic lockdown policy and region-level TFP growth become more flatten when region-level resilience levels are properly taken into account. Moreover, the relative TFP growth effects among the regions with the highest resilience level is higher, as the interaction terms has a positive coefficient (which is significant at 10% level). This result implies that: for the regions with a higher adaptive capacity, it is a better strategy for the government to fight against the COVID-19 pandemic with relatively lower productivity costs by imposing a more flexible lockdown policy.

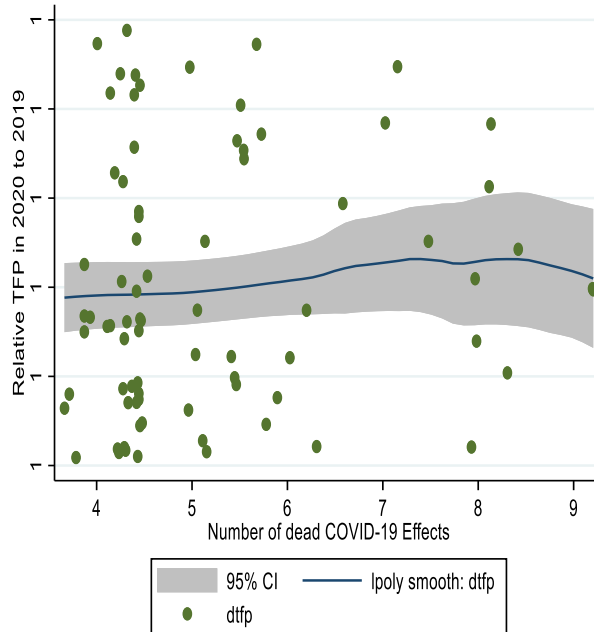## 5. Discussion: Region-level resilience and rural transformation

Maintaining the long-term productivity (in particular, TFP) growth continues to be the most important way for the governments to achieve sustainable economic growth and rural-to-urban transformation in majority Asian, African and
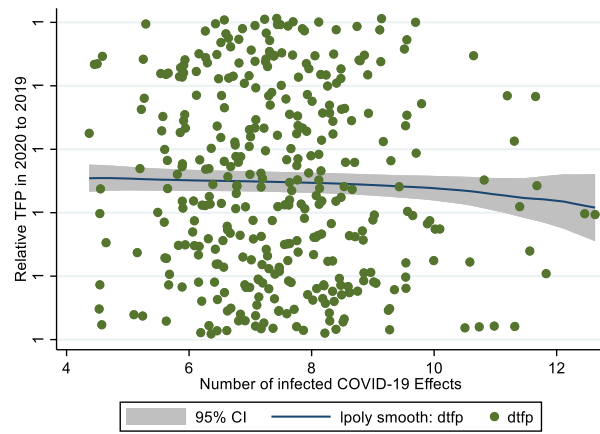
(a) infection cases
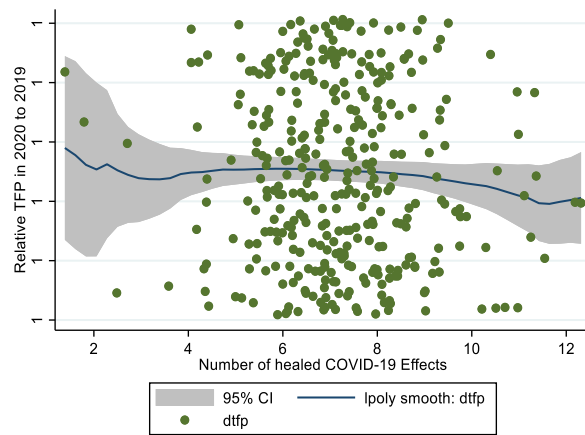
(b) healed cases

(c) dead cases

Fig. 7. The impact of anti-epidemic lockdown policy on the COVID-19 pandemic.
Source: Authors' own estimation.

Table 3
Impact of lockdown policy on COVID-19 TFP effects in China.

	Dependent Variables		
	Infected num. effects (1)	Healed num. effects (2)	Dead num. effects (3)
ControlM	−11.4335***	−10.7863***	−12.7298***
	(1.8041)	(1.9337)	(3.7601)
Constant	8.4836***	8.0079***	2.2182***
	(0.3161)	(0.3834)	(0.5896)
Num. of Obs.	362	362	362
R-squared	0.3026	0.0063	0.1559

Note: Robust standard errors in parentheses, and "***", "**" and "*" represent $p < 0.01$, $p < 0.05$ and $p < 0.1$ respectively.

Table 4
Impact of Quarantine Policy on TFP at the region level in China.
Source: Authors' own estimation.

	Linear Model		Non-linear Model	
	Baseline (1)	With VARint (2)	Baseline (3)	With VARint (4)
Dependent variable: TFP growth in 2020 (ln)				
ControlM	0.250***	0.330***	0.980***	1.110***
	(0.070)	(0.110)	(0.250)	(0.260)
ControlM2	–	–	−2.150***	−2.450***
	–	–	(0.600)	(0.770)
Dummy for Low VAR	–	0.020	–	0.010
	–	(0.010)	–	(0.020)
Dummy for High VAR	–	0.003	–	0.010
	–	(−0.010)	–	(−0.020)
Dummy for Low VAR*ControlM1	–	−0.130	–	−0.100
	–	(0.110)	–	(0.260)
Dummy for Low VAR*ControlM2	–	−0.100	–	−0.200
	–	(0.100)	–	(0.350)
Dummy for HighVAR*ControlM1	–	–	–	0.300*
	–	–	–	(0.130)
Dummy for HighVAR*ControlM2	–	–	–	0.330
	–	–	–	(1.020)
Constant	0.470***	0.460***	0.430***	0.420***
	(0.010)	(0.020)	(0.020)	(0.020)
Observations	362	362	362	362
R-squared	0.106	0.118	0.231	0.246

Note: TFP growth refers to the growth of TFP between 2019 and 2020. Robust standard errors in parentheses, and "***", "**" and "*" represent $p < 0.01$, $p < 0.05$ and $p < 0.1$ respectively.

Latin American developing countries. Apart from declining public R&D spending, more and more emerging challenges come to threaten TFP growth in developing countries contributing the widening productivity gap across countries in recent years. Many recent statistics show that both agricultural and non-agricultural TFP growth are experiencing a declining trend in emerging, and low-income countries for the recent two decades (Adler et al., 2017; Brandt et al., 2020). Among other factors such as lack of public infrastructure, increased degradation of land and water resource and climate change, etc., the unexpected public health crisis like the COVID-19 pandemic, imposed more pressures on the long-term TFP growth. Yet, little is known on how to implement proper policy tools to cope with this type of external shocks in particular when the pandemic becomes an everlasting event.

As an important large developing country, China has made some great achievement in increasing its TFP growth for the past four decades, due to ongoing reforms. In addition, when confronting the COVID-19 pandemic, China also succeeded to bring the first wave of the pandemic within control. However, it is still not known whether China's experiences and lessons in fighting against the COVID-19 pandemic could be applied when the COVID-19 pandemic continued to spread for the third year, and when the policy is to be used by other Asian developing countries. Under this background, we examined the COVID-19 shocks on region-level TFP for 422 regions in China over the period of December 2019–May 2020 between rural and urban areas.

Our results show that the COVID-19 pandemic has on average imposed a negative impact on region-level TFP growth especially in urban China. While the lockdown policy generally helps to relieve the negative pandemic productivity effects, it will cause additional costs for economic recovery through dampening if overused. A good example for our finding is about the recent experience in Shanghai: Although the lockdown policy help to bring the new wave of pandemic under

control, the economic costs are huge. In coping with the new situation, it is essential for government to improve the resilience level of production system in particular in municipal cities. Compared to rural areas, municipal cities are more vulnerable to the pandemic shocks but they can adapt the crisis more quickly if properly managed. These findings provide useful insights for China in near future, as well as for other Asian developing countries, to cope with the second and possibly third waves of the pandemic.

6. Conclusion

In this paper, we explore the impact of the first-wave COVID-19 pandemic on TFP growth in China and assess the role of anti-epidemic quarantine policy in fighting against the pandemic between rural and urban regions with different resilience levels. By combining the daily statistics on the infection with TFP estimates for 442 regions in China for 2020, we find convincing evidence on how the COVID-19 shocks may affect TFP growth across regions differently.

Our results show that the COVID-19 pandemic has generally imposed a negative impact on region-level TFP growth in particular in municipal cities. Although the anti-epidemic quarantine policy helps to bring the COVID-19 pandemic down, but it may incur substantial costs through negatively affecting long-term TFP growth if the lockdown policy is overused. Since the regions with a relative higher resilience level are more likely to cope with the pandemic shocks, a more flexible anti-epidemic policy needs to be designed to fight against the COVID-19 pandemic with lower economic costs (or productivity loss). These findings provide useful insights for China, as well as other Asian developing countries, to cope with ongoing exposure to the epidemic and in designing recovery measures in the post-COVID-19 period.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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